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Lecture Topic 1: Large-Scale Optimization and Learning

Abstract: Many real-world optimization problems involve a large number of decision variables. The trend in engineering optimization shows that the number of decision variables involved in a typical optimization problem has grown exponentially over the last 50 years, and this trend continues with an ever-increasing rate. The proliferation of big-data analytic applications has also resulted in the emergence of large-scale optimization problems at the heart of many machine learning problems. It is this "curse-of-dimensionality" that has made large-scale optimization an exceedingly difficult task. Current optimization methods are often ill-equipped in dealing with such problems. It is this research gap in both theory and practice that has attracted much research interest, making large-scale optimization an active field in recent years. We are currently witnessing a wide range of mathematical, metaheuristics and learning-based optimization algorithms being developed to overcome this scalability issue. This talk will provide an overview of recent advances in this area, covering broadly two parts: (I) learning and exploiting problem structures such as decomposition methods based on variable interaction analysis for large-scale black-box continuous optimization, and (II) problem reduction techniques for solving large-scale combinatorial optimization problems, especially with a focus on leveraging machine learning to enhance our capabilities in tackling combinatorial optimization problems.

Lecture Topic 2: Decision Making in Evolutionary Optimization and Beyond

Abstract: In real-world situations, optimization is rarely done alone without any decision made during the process. Decisions may take the form of preferences supplied by a decision maker or knowledge learnt from prior experience in solving similar problem instances. Very often these decisions play a crucial role in obtaining the kind of optimal solutions we ultimately desire for. If this cannot be done automatically, then human-in-the-loop is often the approach taken to inject preference information that is needed to guide the search. In recent years, we have witnessed the rising popularity of machine learning in facilitating and automating such decision making in the process of optimization, which has a much broader impact beyond just evolutionary optimization. In this talk, I will present several such decision-making facilitated optimization approaches, e.g., using Bayesian optimization to learn the decision maker's preferences interactively in an evolutionary multiobjective optimization algorithm; multimodal optimization using a niching method guided by preference information; employing machine learning to learn from previously solved problem instances (typically combinatorial optimization problems such as the traveling salesman problem), and use such knowledge to build a model to predict the optimal solutions on unseen and much large problem instances. Our "solution prediction via machine learning" approach can be used as a generic problem reduction method for solving some large-scale combinatorial optimization problems and as a warm-start method to meta-heuristics such as ant colony optimization.

Lecture Topic 3: Adaptive Solution Prediction via Machine Learning for Large-Scale Combinatorial Optimization

Abstract: In the big data era, we frequently encounter combinatorial optimization problems of very high dimensionalities. The number of decision variables often exceed thousands or even millions. This poses significant challenges to standard solution techniques such as exact methods (e.g., CPLEX and Gurobi) and meta-heuristics (e.g., evolutionary algorithms), which are usually ill-equipped to cope with the sheer size of such large-scale problems. Meanwhile, machine learning has become increasingly popular as a viable technique to learn and discover problem structure, thereby providing a way moving forward to harness such knowledge for problem decomposition or reduction. The core idea is that if we can decompose a large-scale problem or reduce its size, then it may become plausible again to apply these existing methods. In this talk, I will present our work on "solution prediction via machine learning" for problem reduction, using machine learning models to learn from previously solved problem instances. Furthermore, we use what is learnt from our trained machine learning model to predict whether a decision variable belongs to an optimal solution on unseen and much larger problem instances. Our "solution prediction via machine learning" approach can be used as a generic pre-processing step to substantially prune the search space of a large-scale combinatorial optimization problem. Once the problem is reduced in size, we can then apply standard solution techniques, which hopefully become effective again. We have demonstrated the efficacy of our method for problem reduction over several classic combinatorial optimization problems such as Maximum Weight Clique Problems (MWCP), Travelling Salesman Problems (TSP), and Graph Coloring Problems (GCP). Our recent efforts have been to make such solution prediction methods more adaptive, to allow continuous refinement on the accuracy of the statistical features involved. As a result, the quality of prediction of our off-line trained machine learning model can be further improved.

Lecture Topic 4: Niching Methods for Multimodal Optimization

Abstract: Population or single solution search-based optimization algorithms (i.e., meta-heuristics) in their original forms are usually designed for locating a single global solution. Representative examples include among others evolutionary and swarm intelligence algorithms. These search algorithms typically converge to a single solution because of the global selection scheme used. Nevertheless, many real-world problems are "multi-modal" by nature, i.e., multiple satisfactory solutions exist. It may be desirable to locate many such satisfactory solutions, or even all of them, so that a decision maker can choose one that is most proper in his/her problem context. Numerous techniques have been developed in the past for locating multiple optima (global and/or local). These techniques are commonly referred to as "niching" methods, e.g., crowding, fitness sharing, derating, restricted tournament selection, clearing, speciation, etc. In more recent times, niching methods have also been developed for meta-heuristic algorithms such as Particle Swarm Optimization (PSO) and Differential Evolution (DE). In this talk I will introduce niching methods, including its historical background, the motivation of employing niching in EAs, and the challenges in applying it to solving real-world problems. I will describe a few classic niching methods, such as fitness sharing and crowding, as well as niching methods developed using new meta-heuristics such as PSO and DE. Niching methods can be applied for effective handling of a wide range of problems including static and dynamic optimization, multiobjective optimization, clustering, feature selection, and machine learning. I will provide several such examples of solving real-world multimodal optimization problems.

Lecture Topic 5: From Nature-inspired Computation to Machine Learning

Abstract: Nature-inspired computation and machine learning are two research areas (in Artificial Intelligence) with rising popularity in the past two decades. In this presentation, I will talk about my research experience revolving around these two themes since my time doing PhD until more recently, spanning almost three decades. What started as curiosities and fascination of how nature does computation have gradually evolved into research ideas for designing algorithms in tackling challenging optimization problems. I will touch on the following topics: particle swarm optimization, niching methods, large-scale optimization, preference modelling for multi-criteria decision making, hybridized methods such as meta-heuristics with mathematical programming, and machine learning for handling large-scale combinatorial optimization problems.